Conscious Technology Transfer: AI in Agriculture for Smallholder Empowerment

An Evaluation of Feasibility, Suitability, and Adoption Potential

Bachelor Thesis

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Abstract

This thesis examines the role of artificial intelligence (AI) technologies in agriculture and evaluates their suitability and adoption potential for smallholder farmers. A trend analysis of existing literature analyzed over 20 AI applications and identified the key domains as market information, decision-making, and crop management. Using both the Technology-Organization-Environment (TOE) model and the Technology Acceptance Model (TAM), the applications in the aforementioned domains were evaluated in terms of contextual fit and behavioral adoption.

Findings show that while tools like Amini and Digital Green's Farmer.Chat are theoretically suitable, they often face implementation barriers. Conversely, tools such as Apollo Agriculture and the Rice Crop Manager demonstrate strong adoption potential but require better alignment with smallholder realities.

These results highlight a divergence between technical feasibility and user-context alignment. Therefore, this thesis underlines the importance of conscious technology transfer that takes into account digital infrastructure gaps, training needs, and farmer participation. Only by bridging technical promise with social realities can AI become a transformative force for smallholder resilience and sustainable agriculture.

Table of Contents:

1. Introduction

This thesis explores the role of Artificial Intelligence (AI) in supporting smallholder farmers in the Global South. As general agriculture is adopting this technology to resist climate change and food insecurity, it is essential to assess whether AI can also align with the needs and constraints of smallholder farming systems. The following sections provide background information on smallholders and their challenges, define key terms, and outline the research objectives and structure of the thesis.

1.2 Background

Smallholders are generally defined as farmers located in the Global South who cultivate small plots of land (approximately 2 to 5 hectares), live in vulnerable conditions, and rely on agriculture as their primary source of subsistence and income (Lema et al., 2025). These farmers are key players in the production of many commodities, including coffee, cocoa, and rice, which are now considered nearly irreplaceable globally. Altogether, they produce up to 80% of the world's food, represent 95% of the world's farmers and make up about 55% of the world population who live in poverty (Touch et al., 2024; Natchev, 2024; Heldreth et al., 2021).

Even though smallholders are objectively fundamental actors in general food production, they continuously face multiple interlinked challenges. Economically, small-scale farmers often lack access to formal credit systems and are forced to rely on unofficial resources that charge higher interest rates (Barbier et al., 2015). This perpetuates a cycle of poverty, further aggravated by fluctuating commodity prices, rising input costs, and a general lack of information on the markets they participate in (Barbier et al., 2015). The knowledge gap is unfortunately tied not only to financial and economic matters, but it also includes unawareness of sustainable and efficient agricultural practices and governmental regulations (Gomez et al., 2020). This information void is often filled by middlemen or, in some cases, extension officers that may exploit the farmer, ultimately lowering market participation, crop quality, and quantity. This reduces revenue that could otherwise be reinvested into the land (Gomez et al., 2020).

In addition to financial and informational barriers, infrastructure constraints also play a major role in perpetuating poverty among smallholders. This entails the lack of newer machinery, which could reduce labor and enable higher outputs; limitations in living spaces, which often results in little to no storage space, forcing farmers to sell their produce quickly, often without securing a fair price; and, finally, limited or no access to the internet, which would be able to offer easier communication and information gathering. The value in infrastructure lies in the fact that owning a combination of these could create better understanding of socio-economic circumstances, improve resilience against climate change, and also help generate higher quality produce, such as dried or ground goods, which ultimately enhance the smallholder's competitive edge and contribute to greater economic success. (Gomez et al., 2020)

Another major challenge is the global phenomenon of climate change. It is currently affecting communities in the Global South, through floods, extreme precipitation, droughts, saltwater intrusion in coastal areas, and extreme temperatures. Smallholders are often part of these societies and are directly affected as crop yields, their main source of income, are highly sensitive to changes in temperature and weather patterns. While agriculture in general is being threatened by crops becoming increasingly vulnerable to pests, diseases and natural disasters, which are becoming more frequent due to global climate change, smallholders are already living in these conditions. In many instances, an uninformed response to these adverse conditions is to intensify agricultural practices. While this can improve yields in the short term, it depletes soil fertility in the long run and contributes to increased greenhouse gas emissions, particularly when common nitrogen-based fertilizers are used (Dubois et al., 2024).

Whilst experiencing the negative effects of environmental change, smallholders often lack adequate support or guidance to adapt their agricultural practices. More information is needed to identify which traditional methods are sustainable, and further training is essential to educate farmers to greener methods, particularly where such practices are not yet in use. If no action is taken to support smallholders, food availability and safety will gradually decline. Informed farmers are currently adapting to climate change mainly by implementing agroforestry, which involves planting trees near their cultivated fields to provide shade and nutritional balance to the soil. (Harvey et al., 2018)

While small-scale farmers struggle to stay resilient, the primary strategy for improving agricultural practices, especially in developed countries, has been the application of advanced technologies, such as AI, to create support systems for decision-making, resource and crop management, and much more. This is because its proactive and data-driven approach ultimately translates into rapid adaptations to changes in temperature and a more efficient use of resources. Practical examples are crop health monitoring, optimized irrigation, and improved efficiency in pesticide and herbicide use (Akintuyi, 2024), which can be achieved by implementing different types of AI. These tools can forecast weather patterns, detect diseases or pests, classify weeds, manage water resources, inform farmers' decision-making, and more (Amuda & Rahman, 2024; Van Nieuwkoop, 2025). In these examples optical character recognition, geospatial information systems, drones, robots, predictive algorithms, machine learning, and ICTs are used in combination with AI to improve the efficiency and sustainability of farming practices.

Preliminary results from high-resource contexts have shown positive outcomes in the application of AI in agriculture. As a result, extending these technologies to smallholder farming systems represents a logical next step toward inclusive agricultural innovation. While applying AI technologies can help achieve better working and living standards, it also creates significant concerns about whether it can truly enhance long-term resilience in agricultural markets.

Despite its promise, it is important to highlight that AI contributes to climate change with a significant carbon footprint. Kirkpatrick (2023) showcases how the lifecycle of AI generates emissions especially between data center operations and model deployment. In the context of smallholder farming, this raises important concerns, given that communities are already disproportionately affected by the consequences of climate change. If not developed with attention to sustainability, AI could inadvertently contribute to the worsening of the very conditions it aims to mitigate in this context. Therefore, AI development must prioritize sustainability and environmental accountability, alongside technological innovation.

Furthermore, even if AI tools are developed responsibly, their success depends on whether it respects smallholders' cultural practices, livelihood needs, and allows sufficient time for adaptation and training, given the general digital divide of those communities. An additional concern relates to data privacy risks associated with the use of AI, including the loss of control over personal data, increased vulnerability to cyberattacks, such as denial-of-service or interference with AI-driven machinery, and a deepening of existing inequalities between smallholders and more commercially equipped farmers (Tzachor et al., 2022).

1.2 Research Aims and Key Terms

To better assess the role of AI in smallholder agriculture, this exploratory research aims to identify the main application trends of this technology in small-scale farming contexts and evaluate the extent to which the applications are relevant, suitable, and adoptable. As existing literature primarily focuses on innovation and technical feasibility, the broader impact of transferring a novel technology, namely AI, to communities with low digital literacy, such as smallholders, is often overlooked. Therefore, to explore this intersection and gather a conscious and responsible overview on appropriate practices in transferability for farmer empowerment, the central research question guiding this study is:

What are the main application domains of AI in agriculture, and to what extent are these technologies suitable for smallholder farming contexts and adoptable in practice?

For conceptual clarity, this study defines the following core terms:

- *Conscious*: Refers to a form of technology transfer that is ethically consistent and context-aware. It implies that AI tools should align with smallholder’s needs and challenges, be introduced gradually and accompanied by accessible training and support. A conscious technology transfer respects farmers’ traditions, cultural practices, and living conditions, ensuring that innovations support rather than disrupt their realities.

- *Suitable*: In this thesis, the term refers to how well a technology aligns with smallholder contexts, as assessed through the Technology–Organization–Environment (TOE) framework. A tool is considered suitable when it rates highly across all three TOE dimensions, meaning it is contextually relevant, practically usable by smallholders, and compatible with existing systems and conditions.

- *Adoptable*: This term corresponds to the second framework used in this thesis, the Technology Acceptance Model (TAM). Consequently, a technology is considered adaptable when the tool has already been applied in practice and was perceived as useful, easy to use, and was actually adopted by farmers. It captures the readiness and willingness of smallholders to integrate the innovation into their daily routines.

1.3 Thesis outline

This study conducts a qualitative assessment to answer the central research question. Chapter 2 presents a literature review that outlines the existing AI applications in agriculture, those specifically applied in smallholder contexts, as well as relevant case studies. Chapters 3 and 4 cover, respectively, the methodology and the results and discussion components. These showcase the three analytical tools used to answer the research question, namely a trend analysis to identify patterns in the literature, the TOE framework to assess contextual suitability, and the TAM to examine adoption potential. Finally, Chapters 5 and 6 present the conclusion and future perspectives of AI in agriculture for smallholders.

2. Literature review

The literature review is structured to highlight agricultural AI trends, smallholder-specific approaches, and both academic and commercially driven case studies. Section 2.1 explains how the literature was collected and analyzed, while Section 2.2 presents the key insights and categorization results.

2.1 Literature Selection and review process

Given the extensive literature on AI in agriculture, this section focuses on identifying smallholder-relevant applications that could enhance their livelihoods and working conditions. The following literature review will analyze a broad range of sources that were collected by searching terms like “AI in agriculture for water management”, “Smallholder farmers digitalization”, “AI solutions for smallholder farmers”, “Smallholder farmers challenges”, “How AI is failing smallholders”, “Technology transfer models for smallholders”, “risks/failure of AI for smallholders”, “AI for smallholders”, and finally, “AI in agriculture”.

The data sources were mainly Google Scholar and Google Search. Articles were selected based on their contribution to the key topics of this research and their recency. The selected literature was then categorized into three groups: general AI practices in agriculture, AI practices specific to smallholders, and case studies. The following paragraphs will highlight the main findings.

2.2 Literature Insights

2.2.1 General AI practices for Agriculture

There are many articles on AI technologies for general farming that highlight the opportunities and advantages this technology can bring to agriculture. This enthusiasm is often shared and perceived only by farmers in developed countries with bigger lands and higher investment capital. While this research aims at examining whether these technologies can be effectively helpful to smallholders in the Global South, general research on AI specific agricultural technologies has been done to contextualize solutions brought forth for smallholders. Most research results were peer-reviewed papers in known journals such as Nature or ScienceDirect.

Talaviya et al. (2020) showcases how essential agricultural innovation is in ensuring food availability and safety for the next generations, especially considering the decline in interest in farming and the effects of climate change on weather conditions and groundwater quality. AI technologies enable increased yields, improved crop quality, reduced manual labor, and more efficient use of input resources, reducing overall costs. There are multiple types of AI technologies used together with digital tools to realize these benefits. Talaviya et al. (2020) primarily highlighted machine learning (ML), deep learning (DL) algorithms, computer vision, and analytical models, all of which can support crop management through digital tools, such as sensors, robots, and software.

A review by Akintuyi (2024) highlights the importance of adaptive AI to reduce costs and enhance sustainability of farming practices through the use of big data analytics, ML, DL, sensors, satellite imaging, web-based tools and Geographic Information Systems (GIS). While adaptive AI holds significant promise for transforming agriculture into self-learning systems that use real-time data, the high costs and technical complexity might make it less accessible for many farmers, even if they were interested in innovative solutions.

Finally, Jeffrey and Bommu (2024) further reaffirm the opportunity that AI innovation brings to precision and sustainable agriculture. The technologies discussed include ML, sensors, DL, Computer vision, and more. They all can improve crop management, resource usage, and the sustainability of farming, but, again, adoption barriers, interoperability and data security might pose challenges to adopting smart agriculture, particularly for smallholders.

2.2.2 Smallholder specific AI practices for agriculture

The sources discussed above emphasize that, to date, AI innovation remains accessible to only a limited number of farmers. Yet many of the challenges these technologies aim to solve are currently faced by smallholders, who cannot afford innovation on their own. Building on this idea, several sources emphasize the need for external financial support.

Much of the literature emphasizes the significant potential impact of AI on smallholders' working and living conditions. For instance, Nupo Ventures Team (2024) encourages companies, associations, and governments to support smallholders through digital innovation. By improving crop management and enabling more efficient decision-making, farmers can increase food production and enhance quality for the global population. Assistance needed by smallholders also includes market information and guidance in best practices for quality yield and sustainability.

Amuda and Rahman (2024) reinforce this outlook on AI innovation, as their paper shows how AI can help reach Sustainable Development Goals by improving food production among smallholders. Specifically, computer vision could improve crop management and enable faster responses to climate-related threats. However, the authors stress that supportive governmental policies must be set in place to ensure food security and fair conditions for the farmers.

Some researchers propose integrating smart agriculture with regenerative practices, as discussed by Warrik and Borthakur (2024). These techniques aim for long-term sustainability by seeking to reverse the environmental degradation caused by human activity. The technologies proposed for this are GIS for landscape-level planning, large language models (LLMs) to support information-sharing on financial matters and farming practices, and prediction models for weather and pests.

Although the potential benefits of AI in agriculture are widely emphasized, several sources also highlight the challenges and risks associated with the usage of AI in these contexts. Some papers elucidate that if AI technologies are to be transferred to smallholders, they must be tailored to farmers' specific needs, and implementation risks must be carefully assessed.

Heldreth et al. (2021) and Tzachor et al. (2022) assert that smallholders' conditions are not the most advantageous for technology transfer, as they lack stable internet connection, digital know-how, English or national-specific language skills, and capital to implement AI. However, if developers acknowledge these challenges and co-design systems with farmers, they can build trust within communities by clearly communicating how data is collected and used. This could enable AI to become beneficial for smallholders in the near future. (Heldreth et al., 2021).

Additionally, Tzachor et al. (2022) argue that the data gathered in Smart Agriculture is actually difficult to use in smallholder contexts. This is because the data collected from smallholders is often difficult to interpret, it may require digital transcription and is typically hard to generalize for AI training purposes. Another layer of critique states that over-reliance on data from staple crops and generalized farming techniques can bias AI models, leading them to overlook traditional and polycultural farming systems. Adding to this, Gavai et al. (2025) highlighted how privacy can be breached during data gathering, exposing the farmer's proprietary rights and their compliance patterns to regulations. This shows the necessity to introduce privacy preserving platforms that are set in place to protect farmers, who are already at risk of worsening socio-economic conditions (Taylor, 2022). By ensuring privacy and data security, transparency in the agricultural supply chain can be assured. This, however, may increase vulnerability to cyberattacks and system interferences with AI-driven machinery (Tzachor et al., 2022). A proposed solution to that is to first apply AI in general agriculture by creating "digital sandboxes". These are low-risk hybrid cyber-physical spaces where innovations can be tested in real-life settings, allowing failures to be shared openly and supporting iterative development (Taylor, 2022).

Another viewpoint on the application of AI technology in smallholder contexts is that of Foster et al. (2022). In their paper, they explore how AI may adversely affect smallholder communities, as it could reinforce existing inequalities, especially gender related ones, and perpetuate historical injustices. The solution to this would be taking into consideration the historical context of local communities and, as mentioned before, including smallholders in the developing process.

Lastly, a recent contribution by Shenoy (2025) shows the possible reality of AI applications for smallholders. Although AI promises to improve farmers' conditions, its implementation often appears misaligned with smallholders' actual needs. Many farmers use messaging-based tools to contact communities to solve issues regarding pest identification and generally find the investment in high-tech solutions unproductive, particularly given that many models fail to provide accurate or context-relevant outputs. Other issues related to the implementation are high costs, unsuitable digital infrastructure and data quality, as the AI models are often not trained on the specific crops, or environmental conditions, relevant to their farms (Shenoy, 2025).

2.2.3 Case studies

The research process also identified several case studies that highlight how AI can be applied in smallholder farming contexts. While these examples offer valuable insights into real-world applications, some are presented on platforms owned by the technology providers themselves, which raises concerns about transparency and objectivity.

For instance, Eprod (2024) demonstrates the potential of their digital tools to improve conditions for smallholder farmers in East Africa, especially for supply chain and financial management. Additionally, an interview-based news piece shows that Indian sugarcane farmers benefit greatly from predictive weather tools and a data manager developed by Microsoft, as they improve crop quality and yield, shorten harvest cycles and reduce pesticide and fertilizer use (Yee, 2025). IFAD, or the International Fund for Agricultural Development, also supports the introduction of AI, specifically Microsoft's Azure OpenAI Service. This tool is used to analyze trends and insights within collected data, aiming to make AI generated recommendations understandable, locally relevant, and tailored to farmers' specific crops and regional conditions (Bousios et al., 2024).

Other case studies, or articles, showcase AI applications that can solve various issues for smallholders like climate change, crop and yield management, and, also, market information availability.

ClimateAi, created by Himanshu Gupta, is a web-based tool that helps farmers withstand climate change and assure food security. Together with agriculture, food and beverage corporations, ClimateAi promises to define long-term, precise weather forecasts, helping farmers mitigate risks. (Chhabria & Meineke, 2024)

Van Nieuwkoop (2025) also showcases how AI can effectively empower smallholders against climate change by providing precise weather forecasts. This can significantly impact crop health, as it enables farmers to select optimal times for seeding and fertilizer application, actively avoiding waste. Field tests in India deemed the technology a success and the initiative is being expanded in other areas of the Global South. However, funding is limited and many farmers lack access to adequate resources. According to the article, more climate funding and general investments should be allocated to agricultural adaptation and mitigation, as the initiative impacts climate adaptation and food security.

Another promising initiative aimed at supporting farmers' practices despite climate change is given by Brennan (2018). The article highlights CGIAR's efforts to create an AI model able to predict potential farming outcomes and offer solutions to mitigate risk. While it is still being developed, the platform has been tested on smallholder farmers in Colombia where the AI model correctly predicted weather patterns, saving the farmers from financial losses.

Focusing more on crop and yield management and equal access to information between farmers, web-based decision tools, such as the Rice Crop Manager, are being used. This AI-based tool is able to give specific recommendations, via print-outs or SMS, on the soil's health and nutrition levels which helps increase yields, reduce costs and improve the sustainable footprint of farming practices. (Mishra et al., 2023)

Another technology that aims to improve both yield quantity and quality is weed management through AI systems, which reduces labor intensity and allows for more efficient use of farmers' time and energy. In both Rwanda and Ghana start-ups are developing drones and robots that, together with AI technologies, are able to map weeds and guide machines to apply herbicide to the affected areas. While this has some adoption barriers linked to missing digital infrastructure, there is hope that governments will take action in addressing these issues, ensuring regulated data management and creating financial opportunities that help farmers to invest in these technologies. (Ambali et al., 2024)

Finally, other articles showcase applications that help farmers understand market conditions and manage finances. AI technologies based on Natural Language Processing (NLP) have been shown to reduce information asymmetry, as smallholders are able to dynamically interact with the models and gather information quickly and efficiently (De la Peña & Granados, 2023). The messaging-based tools, trained on data regarding prices, weather, and production techniques, are able to strengthen information security, thereby also supporting trade cycles, and helping smallholders access advisory services, finances and market data on value chains of interest (Natchev, 2024).

An issue related to creating these information models, that was also mentioned before, is smallholder-specific data, which is usually either limited or stored in analog registers. An AI tool that can help access this data is Optical Character Recognition (OCR) technology, which can digitally transcribe paper-based information and then use it to create tailored models for farmers which are more precise and therefore more helpful. (Marie, 2024) This has shown success in a project in Nepal, where analog Nepali records were transcribed and translated into English (Natchev, 2024).

Overall, these case studies demonstrate both the variety of AI's applications in smallholder agriculture and the persistent challenges of affordability, accessibility, and contextual adaptation.

3. Methodology

After exploring the scope of AI in agriculture, particularly in smallholder contexts, through the literature review, this chapter describes the approach used to evaluate its relevance, suitability, and adoption potential. Three analytical components were employed: a trend analysis based on the reviewed literature to identify the key domains of AI; a suitability assessment through the TOE model; and, finally, an evaluation of the adoption potential of selected AI applications through the TAM framework. These technology transfer models were applied to better understand what constitutes a suitable, applicable, and feasible adoption, thereby promoting a more conscious and context-sensitive implementation of emerging technologies.

3.1 Trend Analysis

In addition to the findings presented in the literature review, the collected sources were also analyzed to identify the main trends in AI applications in smallholder agriculture. This was done by mapping relationships between digital tools, AI technologies and the challenges they aim to address. Table A1, A2 and A3 in the Appendix show the data and categorizations used in the network analysis. Specifically, the second table (table A2) presents the 20 sources analyzed, from which 83 connections were identified.
While trying to be comprehensive, the analysis remains limited in its precision, as it was manually developed and examined. Additionally, there is inherent overlap in the data, as single applications often integrate multiple AI technologies, and many innovations address more than one challenge at a time. The application areas themselves may also intersect, as they are not mutually exclusive. They were generally categorized as follows: crop management, which also includes weeding, pest and disease control; water management; market information, including financial opportunities; climate change resistance; and, finally, decision-making assistance, encompassing resource management and techniques that involve sustainable or regenerative practices.

As for digital tools, the selection was based on frequency in the literature. The most commonly mentioned tools include: drones, robots, sensors, messaging-based tools (including chatbots and messaging apps) and web-based tools (which also include visualization apps, software, and online platforms).

The AI technologies, on the other hand, were often generalized in the sources, therefore the main categories selected were: ML and DL, grouped together due to their foundational role in many AI systems and their general applicability; NLP and LLM were combined for their shared focus on language and communication tasks; GIS and computer vision were categorized together based on their use in mapping and spatial analysis; and finally, OCR was classified separately due to its relatively limited appearance in the reviewed sources. Some inputs were broadly classified as ML and DL when the specific AI type was not mentioned, as ML constitutes the underlying framework for a wide range of AI applications.

The visualization of the relationships between digital tools, AI technologies and application areas was carried out using Gephi. The software was employed to generate a network graph that supported the visualization and interpretation of observed trends.

3.2 Technology-Organization-Enivornment Framework

The main AI applications identified in the trend analysis were used to narrow the scope of the suitability evaluation. In this analysis, the TOE framework was used as the primary technology transfer model. This model is generally used to understand how the organizational context impacts the adoption and implementation of new technologies, by contemplating three dimensions, namely *technology*, *organization*, and *environment* (Baker, 2011). Although smallholders are not traditionally classified as business entities, they can be theoretically compared to micro-businesses in terms of reduced size, participation in local economies, vulnerability to environmental changes and limited resources.

In business contexts, the *technological dimension* refers to the possible advantages, complexity, and compatibility of the innovation. The *organizational dimension* highlights the scope of a firm, usually including management dynamics, human resource strategy and organizational culture. Finally, the *environmental dimension* includes physical infrastructure and external force on the firm, such as competitors, customers and socio-cultural issues. (Aligarh et al., 2023) Figure 1 summarizes the key concepts.

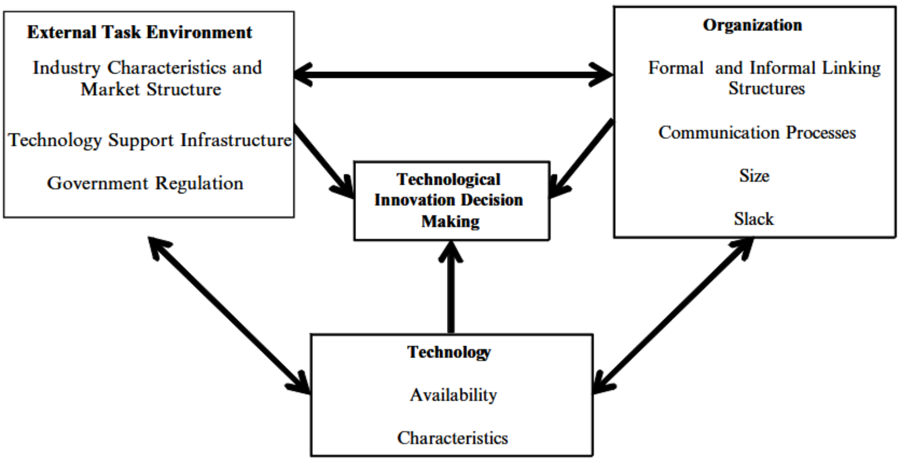

Figure 1: Theoretical TOE framework (Baker, 2011)

Baker (2011) emphasizes how the TOE model can be applied to multiple contexts of diverse nature for research practices. Therefore, this study will apply it to smallholder contexts by considering the *technological element* as the AI application, the *organizational dimension* as the smallholders and the *environmental component* as the market, the stakeholders and the cultural circumstances.

In adapting the TOE model to evaluate smallholder-relevant AI technologies, a high–medium–low scale was developed to assess each of the framework's three dimensions for every AI application. The assessment (see Table 1) was created through a qualitative comparative analysis of over 20 case studies, based on recurring success factors and contextual relevance identified across multiple instances.

Case studies were selected for evaluation if the literature explicitly focused on smallholders and clearly identified central farming challenges.
A "high" rating in the *technological dimension* was assigned when the tool aligned with smallholder needs, had demonstrated tangible results, and was available in local languages with very low entry barriers, such as minimal costs and training requirements (Natchev, 2024; Marie, 2024; Amuda & Rahman, 2024; Talaviya et al., 2020). For the *organizational dimension*, high scores were given to tools that required minimal external assistance, were built on familiar routines, were compatible with devices already owned by smallholders, and clearly addressed day-to-day farming needs (Nupo Ventures Team, 2024; De la Peña & Granados, 2023; Marie, 2024; Farmer.Chat, 2023). Finally, high scores in the *environmental dimension* were assigned when the AI tool had institutional support, complemented weak infrastructure, and contributed to long-term resilience or market access (Natchev, 2024; Marie, 2024; Van Nieuwkoop, 2025; LDRI, 2022). Medium and low scores were assigned to technologies that demonstrated fewer of these qualities or lacked contextual alignment.

To improve readability of the final TOE tables, a traffic light color scheme was used to represent the high–medium–low scale: green for high, yellow for medium, and red for low. Color assignments were based on the majority of characteristics identified in each source. Where this was not possible, the lower grade color was chosen.
Additionally, the tables analyze each AI technology per row, with columns indicating the source, tool name, ratings for the *technological*, *organizational*, and *environmental* dimensions, followed by a notes column providing contextual clarifications or limitations.

Rating	**Qualities for technology**	**Qualities for organization**	**Qualities for environment**
High	Aligned with the specific needs and challenges of smallholders Inclusive of local language Involves low or no entry costs Operable without internet connectivity Demonstrated effectiveness [illegible]	Can be independently operated by farmers Directly addresses key smallholder concerns Compatible with devices commonly available to smallholders Aligns with existing farming practices	Strong engagement from relevant stakeholders Demonstrated collaboration with public or cooperative institutions Contributes to climate resilience and environmental goals Reflects local cultural norms and agricultural traditions
Medium	Partially aligned with smallholder needs and constraints Limited language inclusivity Moderate to high entry cost Requires internet connectivity Limited evidence of effectiveness May require training, though manageable	Usable with limited external assistance Perceived as moderately useful but not critical May necessitate shared use or device upgrades Partially aligned with familiar routines, with some novel components	Stakeholder engagement is present but inconsistent Limited support from institutional or local actors Environmental contributions are suggested but not well-documented May require adjustments to cultural practices or norms Digital infrastructure is underdeveloped External market conditions and resource constraints present periodic challenges
Low	Misaligned with smallholder requirements Restricted language availability Prohibitively high entry costs Reliant on stable internet infrastructure Ineffective or failed in application Technically complex or difficult to navigate	Operationally challenging Perceived relevance is limited or uncertain Requires unfamiliar or cost-prohibitive devices Significantly deviates from established agricultural routines	Stakeholders exhibit low engagement or resistance Lacks institutional or cooperative partnerships No integration of sustainability; potential negative ecological impact Incompatible with local cultural norms and practices Pronounced digital divide

Table 1: TOE assessment table

The results of the TOE assessment are presented in section 4.2, where patterns across the three dimensions are discussed.

3.3 Technology Acceptance Model

While the TOE framework supports an evaluation of suitability and feasibility for conscious technology transfer within smallholder contexts, adoption dynamics are better understood through a behavioural lens. TAM is therefore applied to assess the *perceived usefulness*, *ease of use*, *intention to use*, and *actual use*. The established social-psychology-based model was applied to technology case studies that have reached pilot or practical implementation stages, to gain a richer understanding of AI's adoption potential, while avoiding overgeneralization across diverse contexts.

Figure 2 illustrates the theoretical structure of the framework. The criteria are defined as follows: *perceived usefulness* is regarded as the belief an individual has on whether the innovation could have a positive impact on their situation; *perceived ease of use* is the extent to which the new system is believed to require minimal effort; *intention to use* reflects the individual's intention, or willingness, to adopt the technology; and, finally, *actual use* is determined by the individual's behavior observed in practice. (Davis, 1989)

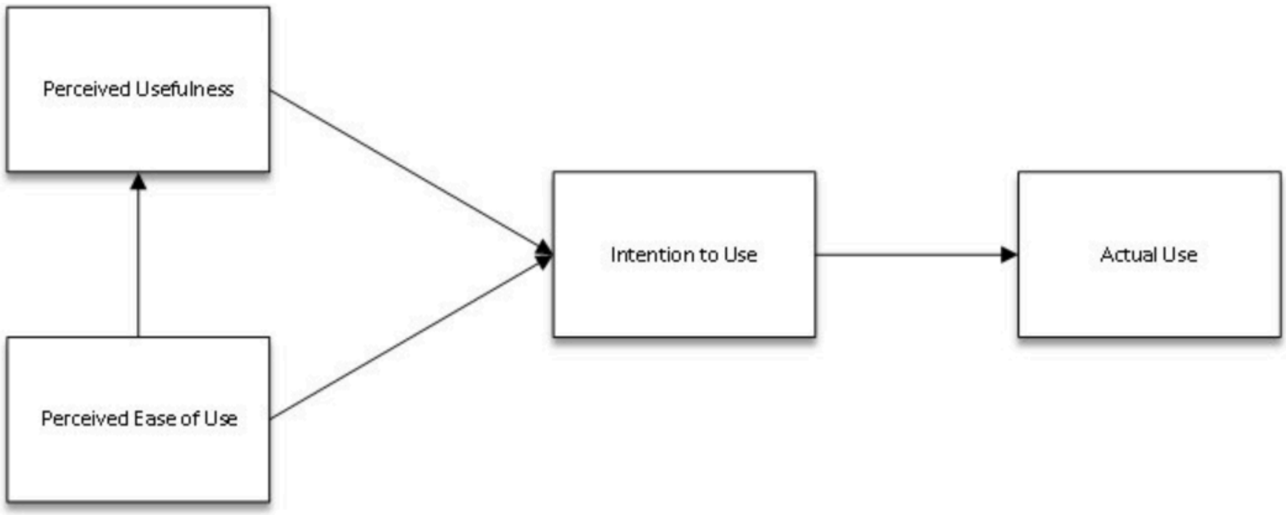

Figure 2: Theoretical TAM framework (Davis, 1989)

The application of this model to the smallholder context shifts these definitions slightly, drawing on the testimonies of farmers from the analyzed case studies, rather than survey-based data. Therefore, an assessment table was created following similar principles to the TOE assessment described earlier. Table 2 showcases the color-coded high-medium-low table, developed through a qualitative comparative analysis of case studies selected for their demonstrated functionality and recurring success patterns. High, or green, rates were given to *perceived usefulness* when technologies had a clear benefit for smallholders, while also solving their challenges (Akintuyi, 2024; Amuda & Rahman, 2024; Van Nieuwkoop, 2025). *Perceived ease of use* was determined as high if the technology could be easily accessed, required low digital skills, and had no costs for farmers (Heldreth et al., 2021; Aligarh et al., 2023; Akintuyi, 2024). A high rating for *intention to use* was applied when significant interest from stakeholders or farmers was indicated, along with increased adoption potential supported by incentives (Natchev, 2024; Harvey et al., 2018). Finally, the *actual use* criteria received a high rating when the technology had already been adopted at scale or showed clear potential to expand across regions within the country (Dubois et al., 2024; Amuda & Rahman, 2024; Touch et al., 2024).

Rating	Percieved Usefulness	Percieved Ease of Use	Intension to use	Actual use
High	Clear and direct benefits for smallholders (e.g., yield improvement or income increase); closely aligned with farmers' needs	Accessible via SMS, USSD, or simple mobile apps; no internet required; minimal digital skills needed; no cost to farmers	Strong interest from farmers or stakeholders; likely to be adopted even without incentives	Widely adopted in real-world settings; scaled use across regions
Medium	Some benefits are observed, but they may be indirect, conditional, or dependent on support; partially aligned with smallholder needs	Requires moderate digital skills; may need training or assistance; interface is not fully intuitive, though generally low-cost for farmers	Interest is present, but adoption may depend on external support, trust-building, or the provision of incentives	Used in pilots or by early adopters; not yet consistently used at scale
Low	Limited or unclear benefit to smallholders; poorly aligned with their priorities	High complexity; requires advanced technology or training; difficult to use without help; cost-prohibitive for farmers	Low or no interest reported; adoption would require major incentives or significant behavior change	No real-world use reported; confined to trials or not adopted after pilot phase

Table 2: TAM assessment table

Unlike the TOE evaluation, which relied on a majority-based rating system, the TAM assessment was interpretive in nature. Each input was rated based on how closely it matched the predefined rating definitions in the TAM assessment matrix. In cases where the available information suggested more than one possible rating, or appeared overly optimistic, the lower score was assigned to ensure a conservative evaluation. This approach allowed for a flexible yet consistent evaluation of adoption potential, while accounting for the inherent subjectivity of qualitative analysis.

The results of this analysis are presented in section 4.3 and visualized in a table where each row includes the source, tool name and main application field of the AI technology, followed by its evaluation across the four TAM categories.

4. Results and Discussion

This section presents the findings of the trend, TOE and TAM analyses, which together aim to answer the research question and identify the best practices for conscious technology transfer in smallholder contexts. The results of the trend analysis influence the identification of case studies for the TOE assessment. Additionally, only the TOE applications that were tested in reality were then examined through the TAM framework.

4.1 Interpreting AI trends in smallholder contexts

The results of the network analysis are shown in Figure 3. The numbers on the arrows indicate the frequency of connections, which is also reflected in the thickness of the edges.

These connections were identified across multiple literature sources. The most frequently discussed combinations include web- and messaging-based tools with ML, DL, GIS, and computer vision, supporting farmers in crop management and decision-making. This trend highlights efforts to address key challenges in agriculture: increasing yields with better quantity and quality, as the human population is growing and food security is being threatened; and sustaining farmers in making various types of decisions to ensure more sustainable practices and efficient use of inputs, ultimately reducing costs.

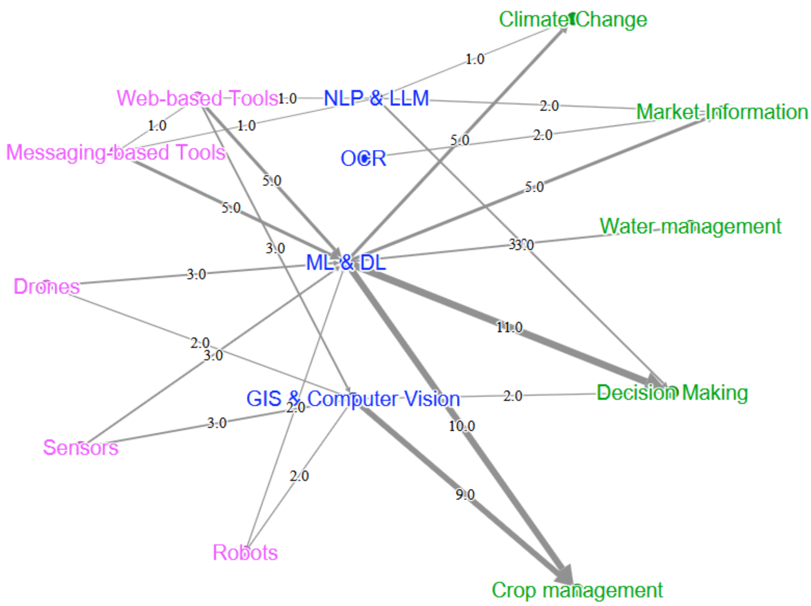

Figure 3: Network analysis of the literature review

While this finding demonstrates growing interest in improving smallholder conditions, it does not convey whether the most popular applications in literature are those that actually reflect farmers' real needs. This is because the majority of the literature often lacks direct input from smallholders.

As described in the methodology, the network visualization was developed using Gephi and is based on 20 sources that formed 83 unique connections. While informative, this network is not a comprehensive representation of the full body of literature on smallholders and may be subject to human interpretation or bias.

To guide the TOE analysis, three key AI application domains were selected based on their frequency in the network: market information, decision-making, and crop management. These domains form the structure of the suitability assessment presented in the next section.

4.2 AI tools suitability evaluation

The TOE framework analyzed the main application areas identified through the trend analysis. Therefore, three tables were created, each corresponding to a key domain: market information, decision making and crop management.

Table 3 summarizes AI applications that support smallholders' access to market and financial information. These tools aim to reduce economic information asymmetry and enable more informed financial decisions. While some overlap exists with general decision-support tools, this table includes only those focused on addressing financial and market-related gaps.

Source	Case	Technology	Organization	Environment
(Natchev, 2024)	Amini *Gives access to finance information via messaing-based tools*			
(Natchev, 2024)	Bolbhav *Mobile platform with real-time information about value chains and markets*			
(Marie, 2024)	OCR-based data gathering *Project in Nepal that uses OCR to get data*			
(Nupo Ventures Team, 2024)	Virtual extension officers *Accessing information and resources that normallly would be shared by middlemen*			
(De la Peña & Granados, 202	Market information systems *Possible chatbots or apps to make information readily available to farmers*			
(Miller-Wise, 2020)	Tulaa *"smallholder marketplace for inputs, credits, advise and market linakages"*			
(Apollo Agriculture, n.d.)	Apollo Agriculture *Agri-fintech company that tries to improve information and fianicing access to farmers*			

Table 3: Summary of TOE Evaluation for Market Information

Table 4 presents AI technologies designed to assist in decision-making, especially those promoting regenerative practices and sustainability-focused agricultural choices.

Source	Case	Technology	Organization	Environment
(Mishra et al., 2023)	Rice Crop Manager *Web-based decision support tool that reccomends best practices*			
(Farmer.Chat, 2023)	Digital Green's Farmer *Provides assistance to extension workers and gives advise to smallholders*			
(Warrik & Borthakur, 2024)	AI for regenerative agriculture *Tools to regenerate nature and create better agirucltural practices for sustainability*			
(van Nieuwkoop, 2025)	AgriLLM *AI initiative to create LLM that support farmers with decision making*			

Table 4: Summary of TOE Evaluation for Decision Making

Table 5 outlines tools for crop management, including solutions for yield forecasting, pathogen detection, and optimization of crop and input use.

Source	Case	Technology	Organization	Environment
(Talaviya et al., 2020)	Disease detection *Use of DL to detected diseases from plant images*			
(Talaviya et al., 2020)	Weed detection *Computer vision application to detect weeds for precise removal*			
(Talaviya et al., 2020)	Yield prediction *ML to forcast yields*			
(Brennan, 2018)	AI-driven decision support for crops *Predictive AI helps in gatheirng information on what, when, how and where to plant crops*			
(Ambali et al., 2024)	Weed management *AI powered detection and removal*			
(Lee, 2025)	Agripiolt.ai *AI platform that gives real-time, farm-specific advise to optimize farming practices*			
(LDRI, 2022)	Early warning system *Access to timely information about weather conditions*			
(Chhabria & Meineke, 2024)	Intelligent crop planning *Deciding what crops to plant, where and when based on AI data*			

Table 5: Summary of TOE Evaluation for Crop Management

While some applications span more than one category, this classification was made to support a structured analysis. The following sections investigate each case study individually to interpret their TOE dimension ratings.

4.2.1 Market Information

Market information tools aim to reduce the financial and informational gaps that smallholders often face by improving their access to price data, input availability, and financial services. These AI-based solutions usually aim at reducing information asymmetry, strengthening farmers' bargaining power, and supporting more effective planning. The following paragraphs examine the relevant case studies, showing how each tool performs across the TOE dimensions in terms of smallholder suitability. The complete, annotated TOE table for this section is available in the Appendix Table A4.

Amini is a messaging-based tool that creates an overview of financial information both for farmers, via SMS or WhatsApp, and stakeholders, such as commercial partners and financial institutions. It aggregates multiple data sources to create useful insights and collaborates with Aon and the African Development Bank to reduce farmers’ financial risk. (Natchev, 2024) This tool scored high across all TOE dimensions, indicating strong suitability for smallholder contexts.

Bolbhav, a mobile platform, aims at supplying data to farmers gathered through real-time information about prices from sale receipts of different value chains. While internet-dependent, it creates an information cooperative by making the entry fee payable either through data contribution, or a minimal financial cost. (Natchev, 2024) The high scores for the *technology* and *organization sections* highlight its ease of use and tangible benefits for smallholders. The *environmental factor* was rated medium, given the often limited data infrastructure in the Global South.

The third entry is primarily a conceptual AI proposal. It suggests the use of OCR to digitize and translate analog registers and data (Marie, 2024). While this technology is mostly beneficial for shareholders and data creation, which may later contribute to improving AI model development, it does not directly address smallholders' immediate needs. Therefore, this application received medium ratings for all domains.

Another proposed AI technology is virtual extension officers. These are developed using LLM systems and NLP technologies to give farmer-specific information and advice. This tool was created because human extension officers, whose availability is increasingly limited, usually share knowledge and sometimes train farmers as well. (Nupo Ventures Team, 2024) The ratings are medium for the *technology* and the *environment sections*, as it is internet dependent, available in major languages and suffers from limited digital infrastructure. On the other hand, the *organizational factor* received a high score, since the application aligns with existing farming routines.

De la Peña and Granados (2023) present chatbot-based AI tools able to provide real-time access to market information. Supported by NLP and topological data analysis, these insights are tailored to farmers' specific needs. This tool scored highly across the *technonolgical* and *organizational categories* for its ease of use, benefits, and mobile accessibility, however a medium rating was given in the *environmental dimension*. This is due to the fact that the data may not align with that of financial institutions and it relies on internet availability.

Tulaa aims to provide smallholder access to financial and market information without using the internet. The system uses AI and mobile technology to become a platform where farmers can buy inputs, connect to sellers and buyers, or apply for loans easily. (Miller-Wise, 2020) While it scores high in both the *technological* and the *environmental* dimensions, given its ease of use, significant value and involvement of stakeholders, it received a medium rating in the *organizational factor*, due to the need for mild training and occasional support.

Apollo agriculture, an agri-fintech company, also offers access to finance and market information. Although results show strong applicability, the company is still solving logistics issues and improving the system. The current tool received medium scores for the *organizational* and *environmental sections*, as it requires occasional assistance and is rooted in the use of the internet, despite its positive contribution to market access. The high score from the *technological perspective* is given due to the low entry cost, proven results, relatively simple interface and the help it provides to farmers.

Among the tools analyzed, Amini emerges as the most suitable one for smallholder contexts. Its user-friendliness and agreements with stakeholders and commercial partners enhance the value of the already much needed financial and market information it provides. While practical implementation outcomes were not explicitly documented, Amini still stands out for its ease of use and smartphone compatibility.

This TOE analysis shows how most market information tools are generally limited by lacking digital infrastructure or minor language exclusion. The digital divide is evident from the frequent medium ratings, particularly in the *environmental dimension*, and is further evidenced by the notes in the annotated TOE table.

4.2.2 Decision Making

Unlike market-focused tools, decision-making applications are built to guide smallholders through day-to-day agricultural choices, ranging from irrigation and fertilizer timing to adopting more sustainable practices. These AI-powered solutions often combine agronomic models with local data to generate tailored advice. The following case studies explore how such technologies perform across the TOE dimensions. The complete assessment table for this section is available in the Appendix (Table A5).

The rice crop manager (RCM) is a web-based decision-support tool that provides insights into nutrient management and recommendations on what to plant, where, and when. The farmer can receive the information either through a print-out or text message. (Mishra et al., 2023) RCM scored high in the *technological* and *environmental domains* given its proven benefits in yield improvement, sustainability, and cost reduction, while also improving the farmer's overall livelihood and productivity. The *organizational factor* received a medium score given the need for occasional support when facing smartphone or connectivity issues.

Another application useful for decision-making practices is Digital Green's Farmer.Chat. This AI assistant aims at providing assistance primarily to extension agents who then provide tailored advice to farmers. Smallholders can also directly access the application but they need internet and familiarity with messaging-based apps. (Farmer.Chat, 2023) The ratings are high for all factors given its effective support and ease of use, whether used directly by farmers or indirectly through extension officers.

AI tools for regenerative agriculture were also suggested. These aim to guide farmers toward practices that improve nature's balance in the long-run (Warrik & Borthakur, 2024). While scoring medium in the *technological section*, given its complex system that still aligns with some smallholder needs, the other dimensions received a rating of low. This is because the system is difficult to use, only marginally useful in current smallholder routines, and not perceived as essential. Furthermore, its divergence from traditional practices and lack of institutional support hinder its practical application.

Finally, Van Nieuwkoop (2025) introduces AgriLLM. This application, developed in collaboration with CGIAR, FAO, World Bank and other relevant players in the industry, aims at creating LLM for easier decision-making practices for farmers and extension officers. The *technical* and *environmental dimension* received a medium rating, due to its internet dependency and limited digital infrastructure. However, the *organizational factor* was rated as high, given its relevance to daily smallholder challenges and its alignment with device usage habits already common among smallholders.

In conclusion, this TOE chart determines Digital Green's Farmer.Chat as the most suitable. This is because this tool offers a wide range of decision-making advice, while accommodating varying levels of digital literacy among farmers. It supports the implementation of more sustainable and gender inclusive practices, has proven results and facilitates a smoother transition toward improved agricultural practices. There are still some challenges regarding the limitations of NLP systems and data availability, but it generally provides great support.

This analysis also highlights recurring trends, such as limited digital infrastructure and the design of AI tools used by both farmers and extension officers. This acknowledges that smallholders may lack the digital familiarity to engage with these technologies directly. It reflects a growing recognition of the diverse realities in the Global South and a shift toward inclusive technology design.

4.2.3 Crop Management

Crop management technologies focus on supporting smallholders in optimizing yield potential, protecting crops, and improving input use efficiency. These AI-powered tools often assist with tasks such as forecasting, early detection of pests and diseases, and providing agronomic recommendations tailored to specific crops or resource conditions. The following case studies examine how such applications perform across the TOE dimensions and whether they align with smallholder needs and realities. The full annotated TOE table for this category is provided in the Appendix (Table A6).

Talaviya et al. (2020) present an AI tool for disease detection that uses DL to identify plant diseases. This aims to reduce farmer workload and increase yields in the long run. However, smallholders may require training to use the system effectively and widespread adoption may be hindered by input scarcity and market pressures. As a result, the tool was rated medium for both the *technological* and *environmental dimensions*. The *organization factor* received a high rating as farmers already own smartphones and the tool directly supports their daily work.

The weed detection tool described in the same study applied computer vision to detect unwanted vegetation. It received identical TOE ratings as the disease detection application: medium for the *technology* and the *environment dimension*s, and high for the *organizational one*. While promising in terms of improving agricultural efficiency, high costs and lack of digital infrastructure may limit scalability among smallholders. (Talaviya et al., 2020)

A yield prediction ML-based application was also suggested. The ability to reduce uncertainty and support short-term planning could be highly impactful for smallholders, as it provides foresight into expected yields and potential market output. All dimensions received medium ratings due to operational complexity and costs that hinder usability, despite the tool's potential to enhance climate resilience. (Talaviya et al., 2020)

The AI-driven decision support tool for crops uses predictive AI to generate recommendations on optimal crop types, timing, and planting locations. This helps in reducing risks posed by climate variability and shifting environmental conditions, while addressing increasing market demands for yield and quality. (Brennan, 2018) This application scored high in the *organizational* and *environmental dimensions*, while the *technological dimension* received a medium rating due to the required training and occasional assistance.

Another weed management technology was presented by Ambali et al. (2024). By using drones which are able to map field conditions, specifically weed infestations, targeted herbicide application can be achieved. This saves money, time and greenhouse gas emissions. The ratings were medium for the *technological aspect*, given that the system integrates advanced technologies, such as drones and robotics, that require internet connectivity. The *organizational* and *environmental dimensions* were rated low. The high equipment costs and lack of financial support hinder adoption, and the system requires significant adjustments to existing farming practices, which is not feasible for most smallholders.

Agripilot.ai is an AI platform that utilizes weather stations installed in local farms, alongside soil samples and satellite and drone images of the farm, to create reliable prediction and alerts on the crop's health. Optimizing farming practices is the goal of this platform and although it has proven results, is accessible via smartphones and potentially helps farmers, its complex system, high entry costs, and high training needs make it unsuitable for smallholders. (Yee, 2025) It was, therefore, rated low in the *technological dimension*, medium in the *environmental category,* and high in the *organizational factor*.

Another tool is an early warning system designed for crop management. This AI aims at supporting farming practices that are efficient and intended to align with precision agriculture. By using satellites, sensors and geo-referenced data, it monitors the farm and provides timely recommendations on optimal farming practices. The tool received medium ratings across all dimensions. While it demonstrates proven results and aligns with farmer needs, including smartphone applicability and climate resilience, its complex, internet-dependent system may hinder independent use by smallholders.

Chhabria and Meineke (2024) also suggest intelligent crop planning as a useful AI tool. It can suggest the best practices and crop types to apply, by forecasting weather patterns and consumers' nutritional needs. Therefore, it can enhance preparedness and yield outcomes. While this sounds promising, this tool was also rated medium in all categories. Despite its potential to support farmers, it is reliant on internet connectivity, may require training, and remains in development.

In conclusion, the crop management TOE analysis once again reveals a significant limitation: limited access to reliable digital infrastructure. Another common limitation is the high cost of associated machinery or subscription fees, which reduces overall suitability for smallholders. The best-performing tool is the AI-driven decision support tool because it relies on an information platform instead of hardware-intensive solutions, like drones or sensors.

Comparing the three TOE tables and keeping in mind the overlap of some applications, the results indicate that the market information AI tools tend to perform better and, thus, appear more suitable for smallholder contexts. While this shows strong potential to reduce information asymmetry, this outcome may be influenced by the evaluation criteria used in this study, the simpler technological setup of these tools, or the literature's focus on information asymmetry as a more readily solvable issue.

In addition to category-specific findings, the cross-analysis highlights broader trends. It shows that tools that require minimal hardware and are compatible with existing farmer devices tend to perform better. Infrastructure gaps and the need for extensive training remain consistent barriers across the categories. Overall, the suitability of the evaluated AI tools remains limited. While the challenges faced by smallholders are increasingly recognized, many solutions still require significant adaptation to become both user-friendly and context-appropriate.

4.3 Assessing adoptability of applied AI tools

The TAM analysis explored the motivational factors influencing the adoption of AI technologies in smallholder contexts. To ensure consistency, only a subset of AI tools previously evaluated through the TOE framework were analyzed, specifically those that had been implemented, either fully or in pilot forms. This selection aligns with the behavioural focus of the TAM framework and the need to assess indicators like *actual use*.

Table 6 presents the summarized TAM assessment, while the annotated version is provided in Table A7 in the Appendix. Although the technologies fall into distinct application domains, they were assessed together to reflect the adaptable nature of the TAM framework. The following paragraphs explain the case studies and their evaluations.

Application	Technology name	Perceived Usefulne	Perceived Ease of U	Intention to Use	Actual Use
Market information	OCR-based data gathering Project in Nepal that uses OCR to get data				
Market information	Tulaa "smallholder marketplace for inputs, credits , advise and market linakages"				
Market information	Apollo Agriculture agri-fintech company that tries to improve information and fianicing access to farmers				
Decision Making	Rice Crop Manager Web-based decision support tool that reccomends				
Decision Making	Digital Green's Farmer Provides assistance to extension workers and gives advise to smallholders				
Crop Management	AI-driven decision support for crops Predictive AI helps in gatheirng information on what, when, how and where to plant crops				
Crop Management	Weed management AI powered detection and removal				
Crop Management	Agripiolt.ai AI platform that gives real-time, farm-specific advise to optimize farming practices				
Crop Management	Early warning system Access to timely information about weather conditions				

Table 6: Simplified TAM table

The OCR data-gathering tool, previously analyzed through the TOE assessment, was applied in Nepal but has not reached widespread adoption yet. Its *perceived usefulness* received a medium rating, as its value lies in digitizing analog data that might otherwise remain inaccessible, and in its potential to serve as a supplementary source of income. Although it does not directly address smallholder farming tasks or challenges, the tool can be easily accessed via Smartphones and applied with varying levels of accuracy depending on language and formatting. This resulted in a medium rating for *perceived ease of use*. The *intention to use wa*s then rated as high, given stakeholders' keen interest in creating more smallholder-specific data and the possibility it offers to access financing tools. Finally, the *actual use* was rated as medium, given its limited application and the presence of some technical issues. (Marie, 2024; Natchev, 2024)

The Tulaa technology was rated high for all of the first three categories. This is because it positively impacts smallholders in financial and managerial tasks, such as planning sales and connecting buyers with sellers. The service offers information for free and sustains its model through transaction-based margins. It uses smartphones, but does not rely on internet connectivity, and has field agents to assist users. The tool has also improved financial access for 71% of farmers in Kenya. Its *actual use* was rated medium, as adoption outside of Kenya remains limited despite promising results (Miller-Wise, 2020).

The decision-making tool Apollo Agriculture received high ratings in all categories. It addresses smallholder challenges and gives them a digital marketplace that is easier to understand, without requiring internet connection. The real-life application documented over

100,000 satisfied users who were able to produce more than doubled their yields. (Apollo Agriculture, n.d.)

Mishra et al.'s RCM also scored high in all domains. This is due to its demonstrated support to farmers that leads to increased yields, reduced costs and improved sustainability. It uses cellphones, does not require internet, and is designed to be user-friendly. It is applied in a range of countries such as the Philippines, Indonesia, Bangladesh and India, and farmers expressed satisfaction.

Digital Green's Farmer.Chat tool scores high in *perceived usefulness*, as it provides tailored advice in local languages based on crop- and location-specific data, helping farmers reduce costs. It received a medium rating for *perceived ease of use* due to its reliance on smartphones and AI apps, where videos on best practices are shared for a one-time fee of $3.50. *Intention to use* and *actual use* were both rated high, given the benefits related to better profits for farmers, the collaborations with governments and World Bank programs, and the proven results in multiple farmer contexts in Ethiopia, Kenya and India. (Farmer.Chat, 2023)

The most adaptable AI tools seem to be the Apollo Agriculture tool and the RCM, given their high scores in all categories.

Across the selected cases, the TAM analysis revealed consistently high ratings in *perceived usefulness* and *intention to use.* Although this may be due to the fact that all tools had real-world applications and targeted improvements in smallholder livelihoods, it can be said that farmers are interested in innovative solutions that could assist them in everyday life. However, the categories of *perceived ease of use* and *actual use* performed rather poorly in comparison. This may be explained by the fact that many tools rely on unfamiliar technologies or digital systems that can be difficult to rapidly introduce to farmers. In many cases, these tools are also quite new and have scarcely been adopted on a large scale. Additionally, availability of training, local language support, and platform accessibility also might have played a role in shaping smallholders' expectations.
Overall, while smallholders show strong motivation to adopt AI tools, widespread success may depend on lowering usability barriers and tailoring technologies to their local contexts.

4.4 Insights across categories and analyses

The thesis's analyses aimed to identify both suitable and adaptable AI technologies for smallholders by combining insights from a trend analysis and the TOE and TAM frameworks.

The trend analysis revealed three dominant domains in agricultural AI literature: market information, decision-making, and crop management. These domains guided the selection of case studies for the subsequent analyses.

The TOE analysis identified tools that appeared highly suitable for smallholder contexts, yet these had not been implemented in practice and were therefore excluded from the adoption-focused TAM analysis. Conversely, the TAM framework highlighted technologies that demonstrated strong adoption potential, but were not deemed fully suitable for smallholder conditions. This contrast is illustrated by the most adaptable tools, Apollo Agriculture (Apollo Agriculture, n.d.) and RCM (Mishra et al., 2023), which performed more modestly in the suitability assessment.

The only case where both suitability and adoption scores were comparably high, though not perfect, was Digital Green's Farmer.Chat tool. This tool performed strongly across the TOE analysis, yet faced moderate limitations in the TAM assessment, especially in *ease of use*, highlighting the importance of balancing user familiarity with digital tools and accessibility. This highlights that adoptability does not necessarily indicate contextual suitability, and that even widely used technologies may face barriers, such as infrastructure constraints or training needs, that hinder their long-term fit within smallholder contexts.

From the combined results of both analyses, it is possible to derive a set of characteristics that define what a consciously transferable AI tool for smallholders should offer:

- Minimal dependency on constant internet access.
- Compatibility with devices already owned by smallholders.
- Interfaces that are intuitive and available in local languages.
- Demonstrated usefulness in improving income, productivity, or sustainability.
- Transitional support mechanisms aimed at improving digital literacy.

Through all the analyses, none of the tools met these criteria. This suggests that while current AI innovations for smallholders show promise, they require further refinement and contextual adaptation.

An additional insight concerns the persistent barrier of inadequate digital infrastructure in many regions of the Global South. This limitation appeared repeatedly in the *environmental assessments* of the TOE framework and also impacted adoption. While AI developers cannot directly address this challenge, it highlights the importance of public-sector investment in digital infrastructure to support inclusive and sustainable technology transfers.

It is also important to acknowledge that the scope of this research was limited to literature-based findings, which often emphasize theoretical potential over validated real-world impact. This limitation further reinforces the need for more empirical research to evaluate the actual performance and adoption of AI technologies in smallholder contexts.

5. Conclusion

This thesis set out to investigate the main application domains and the suitability and adaptability of AI technologies for smallholder farmers by applying the TOE and TAM frameworks across a curated selection of case studies. By combining both frameworks across the same set of tools, this study offers a layered perspective on how innovation can succeed or fail at the smallholder level.

This study first conducted a trend analysis to identify the three most dominant AI application domains, which were: market information, decision-making, and crop management.

The TOE analysis, then, assessed over 20 AI tools to evaluate their suitability to smallholders. While some tools have shown theoretical potential, only a few demonstrated strong contextual fit. These included: Amini (Natchev, 2024), a messaging-based tool providing access to financial information; Digital Green's Farmer.Chat (Farmer.Chat, 2023), a chatbot supporting both farmers and extension officers; and the AI-driven decision support tool for crops (Brennan, 2018), which uses predictive analysis to guide planting decisions.

The third analysis, using the TAM framework, evaluated the adoption potential of a subset of tools that had been implemented in practice, or through pilot initiatives. Surprisingly, it was noted that none of the tools identified as most suitable through the TOE, scored highest in the TAM assessment. Instead, Apollo Agriculture (Apollo Agriculture, n.d.) and RCM (Mishra et al., 2023) were the ones rated highest in the adoptability assessment.

These different results highlight that a digital tool can be perceived as useful and users may express an intention to use it, but it might not be the most tailored to smallholder contexts. Therefore, the findings suggest that suitability without adaptability leaves innovations inaccessible, while adaptability without contextual fit risks deploying tools that do not respond to the actual needs of the farmers. This is why technologies must be transferred consciously to balance contextual fit with innovation and ensure accessibility alongside functionality.

Additionally, the analyses identified general characteristics that an AI tool should possess to be transferred consciously to smallholders. These features include minimal reliance on constant internet access, compatibility with existing devices, interfaces available in local languages, proven usefulness in improving productivity or income, and support systems aimed at building long-term digital literacy rather than dependence.

While this study faces certain constraints, especially due to the limited availability of primary data, the results show that even well-intentioned AI tools often overlook key barriers. This suggests that designing and transferring AI tools to smallholders must take into account feasibility, behavioral factors, and the everyday realities faced by farmers.

6. Future perspective

By comparing suitability and adaptability using two established frameworks, this thesis highlights design-adoption mismatches and offers a dual-lens perspective to guide more inclusive and effective AI development in smallholder contexts. However, several research and implementation gaps remain. This chapter outlines key future directions for research and broader implications for the field.

Without deliberate policy and design intervention, the spread of commercially attractive technologies may hinder conscious technology transfer. This is particularly true when such technologies are poorly aligned with smallholder needs. Emerging trends include data monetization, the growing use of chatbot interfaces, and new efforts to engage youth in farming. These developments may shape the future of AI innovations for smallholders (Natchev, 2024).

To ensure that AI technologies are both climate-friendly and farmer-oriented, future research must address two fronts: environmental impact and local infrastructure.

To facilitate AI adoption in agriculture, it is necessary to reduce its substantial environmental footprint, which is primarily driven by energy-intensive model training. Future research should, therefore, explore strategies to reduce the environmental impact of AI, especially through model optimization and sustainable computing infrastructure. (Warrik & Borthakur, 2024)
Another key factor to study is improving data infrastructure and ensuring that datasets are high-quality, representative, and adaptable to local conditions. This would greatly enhance AI's precision and therefore support farmers' activities. One actionable strategy could be the

creation of village-level digital service hubs, providing training, infrastructure support, and tailored implementation assistance. (Warrik & Borthakur, 2024)

An additional research priority is to promote participatory approaches that involve farmers and intermediaries in co-design and testing processes (Heldreth et al., 2021). This would help ensure both suitability and adoption, given the possibility to receive immediate feedback in development and implementation. Embedding farmer voices in design, aligning innovation with infrastructure realities, and addressing environmental trade-offs will be essential in making AI an equitable force in the future of agriculture.

Further empirical studies are also needed to assess long-term effects of AI adoption among smallholders and to evaluate whether these tools genuinely support them in practice, while considering ethical implications. However, bridging technological potential with social and ecological realities will be key to positioning AI as a genuinely transformative force in global agriculture.

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Appendix

id	label	Type
ML & DL	ML & DL	AI technology
NLP & LLM	NLP & LLM	AI technology
GIS & Computer Vision	GIS & Computer Vision	AI technology
OCR	OCR	AI technology
Web-based Tools	Web-based Tools	Digital tool
Messaging-based Tools	Messaging-based Tools	Digital tool
Drones	Drones	Digital tool
Robots	Robots	Digital tool
Sensors	Sensors	Digital tool
Crop management	Crop management	Challanges
Water management	Water management	Challanges
Market Information	Market Information	Challanges
Climate Change	Climate Change	Challanges
Decision Making	Decision Making	Challanges

Table A1: Edges used for the Network Analysis of the Literature Review

Resource	Source	Target	type	weight
(Nupo Ventures Team, 2024)	Web-based Tools	ML & DL	together with	1
	ML & DL	Crop management	helps with	1
	ML & DL	Water management	helps with	1
	ML & DL	Climate Change	helps with	1
	Drones	GIS & Computer Vision	together with	1
	Robots	GIS & Computer Vision	together with	1
	GIS & Computer Vision	Crop management	helps with	1
	NLP & LLM	Market Information	helps with	1
(Mishra et al., 2023)	Web-based Tools	ML & DL	together with	1
	Messaging-based Tools	ML & DL	together with	1
	ML & DL	Decision Making	helps with	1
	ML & DL	Crop management	helps with	1
(Talaviya et al., 2020)	Drones	GIS & Computer Vision	together with	1
	Messaging-based Tools	ML & DL	together with	1
	ML & DL	Market Information	helps with	1

	ML & DL	Decision Making	helps with	1
	Robots	GIS & Computer Vision	together with	1
	GIS & Computer Vision	Crop management	helps with	1
	Sensors	ML & DL	together with	1
	ML & DL	Water management	helps with	1
(Natchev, 2024)	Messaging-based Tools	ML & DL	together with	1
	Messaging-based Tools	NLP & LLM	together with	1
	ML & DL	Decision Making	helps with	1
	NLP & LLM	Decision Making	helps with	1
	Messaging-based Tools	ML & DL	together with	1
	ML & DL	Market Information	helps with	1
	Web-based Tools	ML & DL	together with	1
	OCR	Market Information	helps with	1
(Warrik & Borthakur, 2024)	GIS & Computer Vision	Crop management	helps with	1
	NLP & LLM	Decision Making	helps with	1
	ML & DL	Market Information	helps with	1
(Marie, 2024)	OCR	Market Information	helps with	1
	Messaging-based Tools	ML & DL	together with	1
	ML & DL	Decision Making	helps with	1
(van Nieuwkoop, 2025)	ML & DL	Climate Change	helps with	1
	NLP & LLM	Decision Making	helps with	1
	GIS & Computer Vision	Crop management	helps with	1
(Brennan, 2018)	ML & DL	Decision Making	helps with	1
	ML & DL	Crop management	helps with	1
(Akintuyi, 2024)	Web-based Tools	ML & DL	together with	1
	ML & DL	Climate Change	helps with	1
	GIS & Computer Vision	Decision Making	helps with	1
	Web-based Tools	GIS & Computer Vision	together with	1
	GIS & Computer Vision	Crop management	helps with	1
	ML & DL	Decision Making	helps with	1
	GIS & Computer Vision	Crop management	helps with	1
	ML & DL	Decision Making	helps with	1
(Lee, 2025)	Sensors	GIS & Computer Vision	together with	1
	GIS & Computer Vision	Decision Making	helps with	1
	GIS & Computer Vision	Crop management	helps with	1
	Web-based Tools	GIS & Computer Vision	together with	1
(Tzachor et al., 2022)	ML & DL	Crop management	helps with	1
	ML & DL	Decision Making	helps with	1
(Foster et al., 2022)	GIS & Computer Vision	Crop management	helps with	1
	Web-based Tools	GIS & Computer Vision	together with	1
	Sensors	GIS & Computer Vision	together with	1
	ML & DL	Crop management	helps with	1
	ML & DL	Climate Change	helps with	1
	ML & DL	Market Information	helps with	1
(Bousios et al., 2024)	ML & DL	Decision Making	helps with	1

	ML & DL	Crop management	helps with	1
(Garbero, 2020)	ML & DL	Decision Making	helps with	1
	NLP & LLM	Climate Change	helps with	1
(LDRI, 2022)	Sensors	GIS & Computer Vision	together with	1
	GIS & Computer Vision	Crop management	helps with	1
(Chhabria & Meineke, 2024)	ML & DL	Climate Change	helps with	1
	ML & DL	Crop management	helps with	1
	Robots	ML & DL	together with	1
	Web-based Tools	ML & DL	together with	1

Table A2: Connections from the literature used for the Network Analysis of the Literature Review

Source	Target	Weight
Web-based Tools	ML & DL	5
ML & DL	Crop management	10
ML & DL	Water management	3
ML & DL	Climate Change	5
Drones	GIS & Computer Vision	2
Robots	GIS & Computer Vision	2
GIS & Computer Vision	Crop management	9
NLP & LLM	Market Information	2
Messaging-based Tools	ML & DL	5
ML & DL	Decision Making	11
ML & DL	Market Information	5
Sensors	ML & DL	3
Messaging-based Tools	NLP & LLM	1
NLP & LLM	Decision Making	3
OCR	Market Information	2
GIS & Computer Vision	Decision Making	2
Web-based Tools	GIS & Computer Vision	3
Drones	ML & DL	3
Robots	ML & DL	2
Web-based Tools	NLP & LLM	1
Messaging-based Tools	Web-based Tools	1
Sensors	GIS & Computer Vision	3
NLP & LLM	Climate Change	1

Table A3: Final connections used or the Network Analysis of the Literature Review

Source	Case	Technology	Organization	Environment	Notes
(Natchev, 2024)	**Amini** *Gives access to finance information via messaging-based tools*	- Aligned with the specific needs and challenges of smallholders - Limited evidence of effectiveness - Intuitive and user-friendly interface	- Can be independently operated by farmers - Compatible with devices commonly available to smallholders - Perceived as moderately useful but not critical	- Digital infrastructure is underdeveloped - Strong engagement from relevant stakeholders - Demonstrated collaboration with public or cooperative institutions	Great potential if internet availability is improved. Helps farmers access market prices more effectively, thereby increasing income. Supported by agreement with AfDB to de-risk farmers.
(Natchev, 2024)	**Bolbhav** *Mobile platform with real-time information about value chains and markets*	- Aligned with the specific needs and challenges of smallholders - Limited evidence of effectiveness - Requires internet connectivity - Involves very low entry costs - Intuitive and user-friendly interface	- Can be independently operated by farmers - Compatible with devices commonly available to smallholders	- Digital infrastructure is underdeveloped - Facilitates improved market access or resource efficiency	Reasonable application of AI and digital technology. Main limitation is internet availability. Supports farmers in evaluating produce prices.
(Marie, 2024)	**OCR-based data gathering** *Project in Nepal that uses OCR to get data*	- Does not really align with smallholder needs and challenges - Inclusive of local language - Requires internet connectivity - May require training, though manageable - Demonstarted effectiveness	- Usable with limited external assistance - Compatible with devices commonly available to smallholders - Perceived as moderately useful but not critical	- Digital infrastructure is underdeveloped - External market conditions and resource (e.g. Data) constraints present occasional challenges	Novel data collection approach could enable AI models to offer tailored insights into financial, market, and farming challenges. Builds on existing data gathering practices to support smallholder-specific tools.
tures Team, 2024)	**Virtual extension officers** *Accessing information and resources that normallly would be shared by middlemen*	- Aligned with the specific needs and challenges of smallholders - Requires internet connectivity - Limited language inclusivity	- Directly addresses key smallholder concerns - Aligns with existing farming practices (e.g. extension officers)	- Digital infrastructure is underdeveloped - Facilitates improved market access or resource efficiency	Limited details available regarding the practical application. If implemented as chatbots or online platforms, it would likely score well in organizational aspects, but lower in environmental factors. Designed to deliver fast and precise information on market trends, financial movements, and agricultural practices.
(De la Peña & Granados, 2023)	**Market information systems** *Possible chatbots or apps to make information readily available to farmers*	- Aligned with the specific needs and challenges of smallholders - Requires internet dependency - Involves no entry costs - Intuitive and user-friendly interface	- Usable with limited external assistance - Directly addresses key smallholder concerns - Compatible with devices commonly available to smallholders	- Digital infrastructure is underdeveloped - External market conditions and resource (e.g. Data) constraints present occasional challenges	Assumes use of chatbots or apps in national languages, limiting access for dialect- or minority-language-speaking communities. Facilitates rapid access to market and pricing data.
Iiller-Wise, 2020)	**Tulaa** *"Smallholder marketplace for inputs, credits, advise and market linakages"*	- Aligned with the specific needs and challenges of smallholders - Operable without internet connectivity - Demonstrated effectiveness - May require training, though manageable	- Usable with limited external assistance - Directly addresses key smallholder concerns	- Facilitates improved market access or resource efficiency - Strong engagement from relevant stakeholders	Implementations in Kenya have enhanced smallholder access to financing. Simplifies entry into financial markets.
Agriculture, n.d.)	**Apollo Agriculture** *Agri-fintech company that tries to improve information and financing access to farmers*	- Aligned with the specific needs and challenges of smallholders - Operable without internet connectivity - Involves very low entry costs - May require training, though manageable - Demonstrated effectiveness	- Usable with limited external assistance - Directly addresses key smallholder concerns	- Digital infrastructure is underdeveloped - Facilitates improved market access or resource efficiency	Applications in Kenya and Zambia show promising results. It enhances access to financial markets. However, logistical challenges persist.

Table A4: Annotated TOE analysis for Market Information

Source	Case	Technology	Organization	Environment	Notes
(Mishra et al., 2023)	**Rice Crop Manager** *Web-based decision support tool that reccomends best practices*	- Aligned with the specific needs and challenges of smallholders - May require training, though manageable - Demonstrated effectiveness	- Usable with limited external assistance - Directly addresses key smallholders concerns	- Digital infrastructure is underdeveloped - Reflects local cultural norms and agricultural traditions - Contributes to climate resilience and environmental goals	Although the source emphasizes women farmers' empowerment, the tool offers substantial benefits for all smallholders. It contributes to increased yields, cost reduction, and improved sustainability. Additionally, it enhances gender inclusivity and facilitates better access to information, ultimately supporting income generation.
(Farmer.Chat, 2023)	**Digital Green's Farmer.Chat** *Provides assistance to extension workers and gives advise to smallholders*	- Aligned with the specific needs and challenges of smallholders - Intuitive and user-friendly interface - Requires internet connectivity - Demonstrated effectiveness	- Can be independently operated by farmers - Compatible with devices commonly available to smallholders - Directly addresses key smallholder concerns - Aligns with existing farming practices (e.g. extension officers)	- Digital infrastructure is underdeveloped - Reflects local cultural norms and agricultural traditions - Contributes to climate resilience and environmental goals	Despite limitations in NLP for certain local dialects, the chatbot is designed with inclusivity in mind. However, data availability remains a constraint. The tool offers tailored advice on markets, soil conditions, weather, and crop practices, while promoting gender-inclusive agricultural support.
(Warrik & Borthakur, 2024)	**AI for regenerative agriculture** *Tools to regenerate nature and create better agirucltural practices for sustainability*	- Aligned with the specific needs and challenges of smallholders - Requires internet connectivity - Technically complex or difficult to navigate	- Operationally challenging - Significantly deviates from established agricultural routines - Perceived as moderately useful but not critical	- Lacks institutional or cooperative partnerships - Digital infrastructure is underdeveloped - Incompatible with local cultural norms and practices	Although promising from a long-term sustainability perspective, this solution does not adequately address the immediate and practical challenges currently faced by smallholder farmers.
(van Nieuwkoop, 2025)	**AgriLLM** *AI initiative to create LLM that support farmers with decision making*	- Aligned with the specific needs and challenges of smallholders - Requires internet connectivity - Technically complex or difficult to navigate	- Operationally challenging - Directly addresses key smallholder concerns - Compatible with devices commonly available to smallholders	- Digital infrastructure is underdeveloped - Demonstrated collaboration with public or cooperative institutions	This tool shows strong potential for success but must carefully consider linguistic diversity and cultural differences among farming communities. It was developed collaboratively with key stakeholders, including CGIAR, FAO, and the World Bank, which may enhance its institutional support and alignment with broader development goals.

Table A5: Annotated TOE analysis for Decision Making

Source	Case	Technology	Organization	Environment	Notes
aviya et al., 2020)	**Disease detection** *Use of DL to detected diseases from plant images*	- Aligned with the specific needs and challenges of smallholders - Requires internet connectivity - Technically complex or difficult to navigate	- Compatible with devices commonly available to smallholders - Operationally challenging - Directly addresses key smallholder concerns	- Digital infrastructure is underdeveloped - External market conditions and resource constraints present occasional challenges	This solution demonstrates strong potential to reduce farmer workload through rapid disease identification and could be scalable in the long term. However, its high cost may limit accessibility. Its adoption may also be driven by increasing market demands for higher crop quality.
aviya et al., 2020)	**Weed detection** *Computer vision application to detect weeds for precise removal*	- Aligned with the specific needs and challenges of smallholders - Requires internet connectivity - Technically complex or difficult to navigate	- Compatible with devices commonly available to smallholders - Operationally challenging - Directly addresses key smallholder concerns	- Digital infrastructure is underdeveloped - External market conditions and resource constraints present occasional challenges	This tool offers promising weed identification capabilities and scalability prospects, but its high cost presents a significant barrier to widespread adoption among smallholders.
aviya et al., 2020)	**Yield prediction** *ML to forcast yields*	- Aligned with the specific needs and challenges of smallholders - Requires internet connectivity - Technically complex or difficult to navigate	- Operationally challanging - Directly addresses key smallholder concerns	- Digital infrastructure is underdeveloped - External market conditions and resource constraints present occasional challenges - Contributes to climate resilience and environmental goals	This technique has the potential to minimize losses and mitigate farming risks by providing accurate yield forecasts. Nonetheless, its high implementation costs may restrict its accessibility to resource-constrained farmers.
(Brennan, 2018)	**AI-driven decision support for crops** *Predictive AI helps in gathering information on what, when, how and where to plant crops*	- Requires internet connectivity - Aligned with the specific needs and challenges of smallholders - May require training, though manageable - Demonstarted effectiveness	- Usable with limited external assistance - Compatible with devices commonly available to smallholders - Directly addresses key smallholder concerns	- Digital infrastructure is underdeveloped - Contributes to climate resilience and environmental goals - Facilitates improved market access or resource efficiency	As illustrated by the case of the Colombian Rice Farmers Federation, this AI-driven solution could significantly support smallholders in adapting to rapidly changing environmental conditions and making informed decisions under uncertainty. Its relevance is further reinforced by mounting market pressures for improved product quality.
nbali et al., 2024)	**Weed management** *AI powered detection and removal*	- Aligned with the specific needs and challenges of smallholders - Requires internet connectivity - Technically complex or difficult to navigate - Demonstarted effectiveness	- Operationally challenging - Significantly deviates from established agricultural routines - Requires unfamiliar or cost-prohibitive devices	- Digital infrastructure is underdeveloped - Lacks institutional or cooperative partnerships	This solution has the potential to substantially enhance smallholders' working conditions. However, its reliance on complex technologies, including drones, robotics, and integrated software, makes it resource-intensive and costly. Ongoing investments in Rwanda and Ghana indicate growing interest, but successful implementation will likely require coordinated financing and institutional support.
(Yee, 2025)	**Agripiolt.ai** *AI platform that gives real-time, farm-specific advise to optimize farming practices*	- Requires internet connectivity - Technically complex or difficult to navigate - High entry costs - May require training, though manageable - Demonstrated effectiveness	- Operationally challenging - Compatible with devices commonly available to smallholders - Directly addresses key smallholder concerns	- Contributes to climate resilience and environmental goals - Digital infrastructure is underdeveloped	Despite its high cost, this initiative appears to empower farmers by reducing risks associated with adverse weather conditions and disease outbreaks. It leverages a complex system involving satellite imaging and sensors, which may pose adoption challenges for resource-limited users.

Table A6: Annotated TOE analysis for Crop Management

Source	Application	Technology name	Perceived Usefulness	Perceived Ease of Use	Intention to Use	Actual Use
(Marie, 2024); (Natchev, 2024)	Market information	**OCR-based data gathering** *Project in Nepal that uses OCR to get data*	Helps formalize business in a universal format; Creates data for agencies to create valuable products and services for farmers; Creates data for better AI models; Can be an extra income stream	Accessed via phone camera (easy), but photo capture, language and formatting can impact the accuracy of the tool; Seems to use cooperative staff which requires some training and not farmers due to possible digital divide	Stakeholders see big potential especially with being able to access data on smallholder farmers; Is highly relevant for farmers as it can help them access loans, pricing tools and general business managment	Not widespread adoption yet; The pilot tests seemed promising in extracting and structuring data and actively giving smallholder a digital footprint.
(Miller-Wise, 2020)	Market information	**Tulaa** *"Smallholder marketplace for inputs, credits , advise and market linakages"*	Helps farmers by providing inputs, credit, agronomic advice and market linkages; Connects suppliers to sellers; Effectivly helps planning sales of the crops	Uses cellphones and does not require interent; Information is sent via SMS or call; Prepared field agents recruit costumers and register them; Tulaa take a margin from inputs sold, credits and on produce sale; Information is free	Early user feedback was positive; Adoption was easy considering low digital literacy; Before Tulaa, 71% of the farmers had never accessed input financing before	Target demographic is smallholders with 2-2.5 hectars; Mainly focusing on Kenya; 84% of farmers self-reported higher incomes; 15.000 farmers participated in the pilot run
(Apollo Agriculture, n.d.)	Market information	**Apollo Agriculture** *Agri-fintech company that tries to improve information and financing access to farmers*	Helps farmers to access quality resources, credits and market information; increases yields; basically serves as a marketplace were farmers can buy either in cash or credit	Uses cellphones; Information is availabe through SMS, USSD and an app; Field agents are also employed for personalized support	Benefits include increased yields and income; Farmers also access credits and financing opportunities	Over 100.000 satisfied farmers that are growing over the years; on average framers seem to create 2.5 times more produce
(Mishra et al., 2023)	Decision Making	**Rice Crop Manager** *Web-based decision support tool that reccomends best practices*	Helps farmers increase yields and reduce costs; contributes to creating sustainable practices	Uses cellphones; Information is available through SMS and printouts; easy to understand recommendations	Benefits include increased yields, better quality and reduced costs	Used in the Philippines, Indonesia, Bangladesh and India, confirms the promises made of reducing cost and increasing yields
(Farmer.Chat, 2023)	Decision Making	**Digital Green's Farmer.Chat** *Provides assistance to extension workers and gives advise to smallholders*	Helps farmers with advice in their local language, using also location and crop-specific data; Cost reduction; Increases income and production	Uses smartphones and easy-to-use AI-based apps; Often shares videos on best practices to apply which are easy to understand and available in 40 languages; Cost is of 3.50$	Benefits are multiple and mainly related to better profit; Farmers will need low levels of digital literacy; program collaborates with governmanets and World Bank programs	Increased income up to 24% and increased production up to 17%; Success stories are multiple and are mainly centered around Ethiopia, Kenya and India
(Brennan, 2018)	Crop Management	**AI-driven decision support for crops** *Predictive AI helps in gathering information on what, when, how and where to plant crops*	Helps farmers with seasonal forecasts so they know what to plant and when; increases yields, reduces costs and so increases income security	AI systems that use various data can require training and higher levels of digital literacy; Article does not clearly state what the interface is but suggests middlemen that share the information with farmers	Potential benefits and risk reduction are strong motivators for smallholder to deploy this technology; Collaborations with the private sectors are mentioned to increase chances on using this technology	Pilot project was successful in securing income to rice farmers in Colombia; actively reduces risks while providing critical advice to real problems
(Ambali et al., 2024)	Crop Management	**Weed management** *AI powered detection and removal*	Helps farmers by increasing yieds and their quality, reducing water usage and working hours; improves environmental sustainability	Use AI-equipped drones or robots that either autonomously remove the weeds or map where they are for manual removal; Start-up based initiatives with collaborations with governaments and private sector; Training is needed to use these tools	High interest from governaments and private stakeholders; benefits farmers undoubtly but is quite costly and difficult to implement; Financial support is crucial	Rwanda and Ghana are piloting the technologies but there are no clear results on broader applications
(Lee, 2025)	Crop Management	**Agripiolt.ai** *AI platform that gives real-time, farm-specific advise to optimize farming practices*	Helps farmers obtain more yield of better quality; Improves decision making which reduces input costs; Insights are personalized to the farm's needs	Smartphone app gives insight to the crop managment tool; training is needed even though for usual smartphone users it is easy; Cost is 117$ for one-time soil test and training fee	Clear benefits for farmers; 20.000 farmers signed up for trail run; collaborates with Micorsoft and ADT	Actively used in India; Farmers report 2.5x higher yields; scaling is happening with governament and coopertives
(LDRI, 2022)	Crop Management	**Early warning system** *Access to timely information about weather conditions*	Increases food and nutrition security; Helps farmers identify best practices to plant the crops; provides information about the right inputs and about revelant events happening in the area;	Uses smartphone platforms designed for low digital literacy; provides real-time alerts and information; Used by both farmers and stakeholders; Co-deisgn and co-developed with farmers	Clear benefits for farmers; Governaments and cooperatives support the project	Piloted in Keya; Still at an early stage but showcases strong engagement and potential

Table A7: Annotated TAM table